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Drought in the city: The economic impact of water scarcity in Latin American metropolitan areas

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ABSTRACT

While the harmful impact of droughts is well-documented in rural areas, how droughts affect cities' economies remains an open question. Using monthly labour force surveys from 78 cities in Latin America, we demonstrate that large sustained dry events decrease the probability of being employed, hourly wages, hours worked, and labour incomes. Informal workers are impacted the most. We highlight that the impact of droughts is larger than the impact of wet events, like those that cause floods. Health and power outages are two pathways explaining our results. Climate change will increase the occurrence of droughts, making our findings particularly relevant.

> You take delight not in a city's seven or seventy wonders but in the answer it gives to a question of yours.
>
> —Italo Calvino, Invisible Cities

1. Introduction

Urban growth is a thirsty business. The increase in urban inhabitants from 54 percent in 2014 to an estimated 66 percent by 2050 (UN-ESA, 2014) is projected to increase cities' demand for water by 50 to 70 percent (Lundqvist, Appasamy, & Nelliyat, 2003; McKinsey, 2009). Yet, one fourth of cities around the world are already water stressed and exposed to perennial water shortages (McDonald et al., 2014).[1] With climate and land use changes, even river basins with important reserves of freshwater, such as in São Paulo or Cape Town, have experienced major droughts over the last years, leading to drastic water shortages. To what extent water availability matters for economic activity in urban settings remains largely unknown. We highlight in this paper that droughts can significantly harm the economic activity of large metropolitan areas. Our results even suggest that the magnitude of the impact of droughts is significantly larger than the impact of wet shocks, like those that cause floods.

Our paper focuses on Latin America, the second most urbanised region of the world after North America (82 percent vs 80 percent, UN-ESA 2014). Our research uses monthly microeconomic labour market data from 78 of the largest cities on the continent between 2005 and 2014. We spatially join them with global gridded weather data from 1900 to 2014 using the centroid of each metropolitan area, allowing us to construct exogenous indexes of droughts based on abnormal deviations from long term means of rainfall. In this natural experiment setting, we show that large and sustained dry shocks (droughts) negatively impact economic activity. Our identification strategy consists in comparing labour market outcomes during drought months and near-normal weather months from workers living in the same city during the same year. During droughts, the probability of an active worker to be employed decreases, as well as the number of hours worked, the wages and the labour incomes of informal employed workers. Our results are robust to several specifications and alternative measures of droughts. They also hold when using different datasets (household surveys, administrative data on the universe of formal Brazilian firms, Enterprise Surveys data), all covering different cities and different periods of time.

There are several reasons to expect such a negative impact of droughts on cities' economies. Hydropower still generates more than 50 percent of electricity in Latin America (Al-mulali, Fereidouni, & Lee, 2014). Generally speaking, water is one of the principal inputs to generate electricity, even beyond hydropower.[2]

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[1] McDonald et al. (2011) modeled results show that currently 150 million people live in cities with perennial water shortage, defined as having less than 100 L per person per day of sustainable surface and groundwater flow within their urban extent. By 2050, demographic growth will increase this figure to almost 1 billion people. They predict that climate change will cause water shortage for an additional 100 million urbanites.

[2] The cooling of many coal, nuclear power plants require hundreds to thousands liters of water per megawatt of electricity produced (Meldrum et al., 2013).

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0305-750X/

Consequently, water scarcity can lead to electric shutdowns as was recently seen in India or in Brazil.[3] Using Enterprise Surveys for 22 Latin American and Caribbean Countries, we highlight that droughts significantly increase power outages for firms.

The health literature also points out the negative effects of droughts on health conditions as droughts increase the risk of diarrhea, infections and the survival rate of vectors of diseases (Kovats, 2003), notably in developing countries (Lohmann & Lechtenfeld, 2015). Cities' higher population density favours the rapid spread of diseases compared to rural areas, particularly in the absence of adequate sanitation and sewerage for all households (Ashraf, Glaeser, & Ponzetto, 2016). With a panel of hospital admissions data from Brazil, we also find a worsening of health conditions when droughts occur. This deterioration of health can have direct consequences for labour productivity.

There is a consensus among policy makers that cities are vulnerable to floods. Our empirical model allows us to compare directly the impact of droughts with the impact of similar wet shocks, including wet shocks of an intensity that can cause floods. Compared to droughts, we do not find that large wet deviations cause a general decrease in employment. Also, when large repeated dry shocks decrease monthly labour incomes by six and a half percent, similar wet shocks decrease monthly incomes by two to four percent. Consistently with this finding, both the impact of wet shocks on power outages and health outcomes are smaller than the impact of symmetric dry shocks. While floods tend to attract most of the media attention as a result of their more destructive destruction power (Eisensee and Strömberg, 2007), our paper emphasises the importance for cities to protect themselves from droughts as well.

Our results are striking as Latin America has the highest infrastructure density among developing regions, in spite of its own infrastructure gap.[4] In a recent working paper, Ashraf et al. (2017) find that water outages in the city of Lusaka, Zambia, negatively affect health outcomes and reduce the quantity of financial transactions. Arguably, the quantity and quality of infrastructure in Latin America is better than in less developed countries such as Zambia. Yet, our results show that the problem of water in cities is true for middle incomes countries, and not only in low-incomes countries. Our results also show that the negative economic impact of water scarcity is true at a large geographic scale (one region compared to one city).

The remainder of the paper is organised as follows. Section 2 presents the literature. Section 3 describes the data and the empirical strategy. Section 4 presents our results on the impact of shocks and section 5 analyses pathways. Section 6 discusses the findings and concludes.

2. Prior research

An important literature analyses the impact of positive and negative rainfall shocks on agricultural activity. It shows that even shocks of a small magnitude have important consequences on yields (Zaveri, Russ & Damania, 2018). Droughts then translate into increases in poverty and decreases of key development outcomes such as health and education in developing countries (Kazianga & Udry, 2006; Dercon, 2004), with possible long-term consequences (Dinkelman, 2017; Shah & Steinberg, 2017). For example, it has been shown that rainfall variability impacts agricultural wages (Mueller & Quisumbing, 2011), food prices (Hill & Porter, 2017), gender wage gap (Mahajan, 2017), land invasions (Hidalgo, 2010), local tax revenues (Sanoh, 2015), violence towards women (Sekhri & Storeygard, 2014), and has accelerated the spread of HIV (Burke, Gong, & Jones, 2015).

In comparison, the literature on rainfall shocks in urban areas is more limited. At the city level, looking at 1800 cities between 2003 and 2008, Kocornik-Mina et al. (2015) show that large scale floods (i.e. those displacing more than 100,000 people) reduce night-time lights by two to eight percent within cities the year of the flood, but that even hard-hit cities recover within one year. Acevedo (2015) finds similar results on the impact of floods and on the speed of recovery using microeconomic data on labour markets outcomes in the Colombian Caribbean. Chen (2017) additionally find a small effect of floods on internal migration in Bangladesh. For dry shocks, existing research has shown an indirect effect of droughts on cities. Rural-urban migration increases with droughts as in Africa (Henderson, Storeygard, & Deichmann, 2017; Gray & Mueller, 2012) and recently in Syria (Kelley, 2015). Urban centres are then affected by droughts in the long term due to an accelerated sector reallocation. A rich literature shows that droughts increase the probability of conflicts (Miguel, Satyanath, & Sergenti, 2004; Jia, 2014; Couttenier & Soubeyran, 2014). Almer, Laurent-Lucchetti, and Oechslin (2017) show that the relationship is particularly true in areas close from cities. Again, one might then expect consequences of these conflicts on labour market outcomes.

The literature highlighting a direct economic impact of water scarcity on cities is thin. The closest paper from ours is Ashraf et al. (2017). The authors study the impact of water outages in Lusaka, Zambia. They demonstrate that water outages increase the incidence of diseases (diarrhea, upper respiratory infections, typhoid fever and measles), which translate into a reduction of money-banking transactions and into an increase in the time that girls spend at their chores. If our conclusions converge with Ashraf, Glaser, Holland, et al. (2017), the two papers differ in several ways. When Ashraf et al. (2017) test the impact of water outages using data from the main service provider of water, our paper uses rainfall data. Our paper also adds at least three insights to Ashraf et al. (2017)'s findings. First, we show that not only money banking is impacted but labour market more globally. Second, we add a second pathway to explain the results by demonstrating that power outages for firms increase with droughts. Third, while Ashraf et al. (2017) highlight an impact of droughts in a city with poor infrastructures from one of the least advanced economy on the planet, we show convergent results for cities richer in infrastructures from middle income countries. Hence, our findings suggest that a broad range of countries can suffer from droughts. Our paper is also related to Mueller and Osgood (2009). The authors find a negative impact of negative shocks on wages in rural Brazil using survey data between 1992 and 1995. They are however unable to confirm a direct impact of droughts on wages in urban areas, contrary to our findings.

Our paper also relates to the Climate-Economy Literature (Hsiang, 2010; Hsiang, 2016; Carleton & Hsiang, 2016) that has more recently pushed towards the exploration of the role of temperature as a proxy for climate variations (Dell, Jones, & Olken, 2012; Graff Zivin & Neidell, 2014; Burke, Hsiang, & Miguel, 2015). In particular, Graff Zivin & Neidell (2014) use US daily temperature and individual data from the 2003–06 National Time Use Surveys to show that positive temperature shocks lead to substantial changes in labour supply. Those results echo those found at the macroeconomic level where patterns of responses to variation in temperatures are consistent with labour effects (Hsiang, 2010; Deryugina & Hsiang, 2014; Burke et al., 2015).

Finally, our approach is connected to the literature on large natural disasters. This literature finds mixed impacts of shocks on labour market. In Indonesia, Kirchberger (2017) finds labour mar-

[3] See: http://www.wri.org/blog/2015/06/global-tour-7-recent-droughts and http://www.theguardian.com/world/2015/jan/23/brazil-worst-drought-history.

[4] Fay et al. (2017) notes that some 17 percent of Latin Americans have no access to a private, improved sanitation facility and one-fifth of them still practice open defecation. Additionally, only about a third of wastewater is treated.

kets to be rather resilient to earthquakes and even a positive impact on wages for agricultural workers, driven by a labour supply reallocation towards the construction sector. Those findings echo those of Belasen and Polachek (2008) and Belasen and Polachek (2009) who look at the impact of hurricanes on labour markets in Florida and identify a positive impact on wage but a slower growth in employment in counties directly hit. In Guatemala, Baez et al. (2016), look at the impact of tropical storm Agatha (2010). They find that households in urban areas bore the brunt of the burden with their per capita expenditure falling by over eight percent.

3. Methods

3.1. Main datasets

The main result of our paper are obtained by combining two sets of data: micro data on labour market outcomes and gridded weather data. Data on labour market outcomes come from the Labour Database for Latin America and The Caribbean (LABLAC) initiative. LABLAC is a joint project conducted by the Centre for Distributional, Labour and Social Studies (CEDLAS) at the University of La Plata (Argentina) and the World Bank. It aims to harmonise the different labour force surveys conducted in the region. It includes information from over 300 labour surveys carried out in 24 Latin America and Caribbean countries since 2005.

We construct our dataset by focusing on all the rounds of surveys that are representative at the metropolitan area level. Our combined repeated cross-section dataset covers around 13 million active individuals living in 78 metropolitan areas from nine countries (Brazil, Chile, Colombia, El Salvador, Ecuador, Mexico, Paraguay, Peru, and Uruguay). We focus on individuals that are between 16 and 60 years old. We track information on their employment status (whether they are employed or not), on the number of hours they worked, and on their hourly wages. Our dataset is monthly and covers the full period between 2005 and 2014 for most countries. Our sample is representative of a population of about 300 million active people living in the biggest cities from these nine countries, that is about half of the total Latin America population. Table A1 in Appendix summarises the different rounds of surveys used in this study.

Rainfall data come from the University of Delaware's Global Land Temperature and Precipitation Data (Willmott, Matsuura, & Legates, 2001). This gridded dataset contains monthly observations of precipitations (in mm) and of average temperatures (in C) at the 0.5-degree grid cell level (approximately 50 km at the equator) from 1900 to 2014. We determine the centroid of the 78 metropolitan areas studied here using Open Street Map. We spatially join them to the gridded weather data so as to determine weather conditions in each metropolitan area.

3.2. Empirical strategy

We aim to measure the impact of droughts on labour market outcomes. In this subsection, we explain how we measure droughts and we present the empirical model.

3.2.1. Droughts

The Oxford dictionary defines droughts as "prolonged periods of abnormally low rainfall, leading to a shortage of water".[5] Droughts are the combination of two dimensions: an abnormal level and a time dimension. The literature often considers a level of rainfall as abnormal when it lies one or two standard deviations below the long-term average observed in the area. We follow this approach.

Incidentally, we proceed in two ways to define droughts using monthly data. First, we define two levels of abnormality for rainfall. We define as small shocks variations of rainfall between one and two standard deviations from the average of rainfall for a given month in a specific city between 1900 and 2014. We define as large shocks deviations of rainfall larger than two standard deviations from the long-term average of this month in this city. By doing that, our measure of abnormality is month and city specific and takes into account seasonality of rainfall and systematic differences of precipitation level between cities. Second, shocks need to be sustained over a prolonged period of time to cause a drought. We construct droughts variables by counting the number of consecutive months during which levels of rainfall are abnormal. We start by looking at the impact of shocks of a length up to two months -a number that allows us to have sufficient observations for large shocks.

Calling $S^k_{j,m}$ a rainfall shock of intensity $k = 1,2$ in city j during month m, our variable $Drought^k_{j,m}$ is such that:

$$Drought^{k=1,2}_{j,m} = \begin{cases} 0 \ if \ S^k_{j,m} = 0 \ \& \ S^k_{j,m-1} = 0 \\ 1 \ if \ S^k_{j,m} = 1 \ \& \ S^k_{j,m-1} = 0 \\ 2 \ if \ S^k_{j,m} = 1 \ \& \ S^k_{j,m-1} = 1 \end{cases}$$

where $k = 1$ refers to small shocks and $k = 2$ refers to large shocks. m does not stand for the 12 calendar months but represents each of the 120 months covered by our study. As a robustness, we define only one threshold based on the one standard deviation threshold for shocks and extend the period for up to four months. Our empirical approach presents different advantages. First, we could have used level of rainfalls instead of deviation of rainfall to study the impact of water availability. However, we know that population dynamics and urbanization have historical origins born out of deliberate choices to establish cities in locations where climate is the most favourable to economic activity. This means that current levels of economic activity and levels of rainfall are potentially endogenous. Using local random month-to-month deviations of rainfall allows to overcome this issue and obtain causal results on water availability. Second, measuring droughts using rainfall data allows to construct wet shocks symmetric to dry shocks. In a unique framework, we can then compare directly the economic consequences of droughts to the economic consequences of wet spells, including wet spells large enough to cause floods. Hence, we construct small and large wet shocks symmetric to dry shocks, knowing that large wet spells correspond to the kind of rainfall shocks that would be expected to result in floods and landslides.[6]

3.2.2. Equation

To estimate the effect of droughts on labour market outcomes, our baseline model is:

[5] See: https://en.oxforddictionaries.com/definition/drought.

[6] EM-DAT is a global database on natural and technological disasters, containing essential core data on the occurrence and effects of more than 21,000 disasters in the world, from 1900 to present. EM-DAT is maintained by the Centre for Research on the Epidemiology of Disasters (CRE D) at the School of Public Health of the Université Catholique de Louvain located in Brussels, Belgium. In Latin America over the period covered by our study, large wet shocks are associated with floods events that happened for example in Colombia in 2005, in 2008, in 2009 and in 2011. Each time, those floods affected between 475,000 and 2.4 million people according to the EM-DAT dataset that tracks natural disasters. Despite disrupting daily life and potentially economic activity, each large wet spells has not resulted in important floods recorded by EM-DAT.

$$\ln\,(Labour\ Outcome)_{i,j,m} = \beta\ Drought^{k}_{j,m} + \tau_1 Temperature^{k}_{j,m} + \tau_2 Temperature^{k}_{j,m-1} + \eta_{j,y} + \mathrm{X}_m + \epsilon_{i,j,m,y}\ \text{ for } k = 1, 2 \quad (1)$$

where $Labout\ Outcome_{i,j,m}$ is the labour market outcome for individual i living in city j during month m. This labour market outcome can be whether the individual is employed or not, the logarithm of her/his hourly wage expressed in 2005 PPP, the logarithm of the number of hours worked during the month and the logarithm of her/his monthly labour income. We control for temperatures (in C). This matters as rainfall, temperatures and economic activity are correlated (Auffhammer, 2013; Hsiang, 2010; Dell, et al., 2012). We include city by year fixed effects to control for time-invariant city-specific characteristics during the year ($\eta_{j,y}$). Month by year fixed effects control for monthly variations common to the region (X_m). We cluster standard errors at the city level to respect the quasi-experimental design of the study (Abadie, 2017). Our estimation strategies hence compare labour market outcomes during months with droughts and months with a near-normal weather in a given city during a given year.

Because droughts are by construction exogenous, we do not need to control for individual characteristics (age, education, gender) to identify the impact of droughts on individual labour market outcomes. Our baseline model only includes shocks and not individual control covariates, consequently avoiding the "bad control" problem (Angrist & Pischke, 2008). As a robustness check, we add individual controls to estimate a standard Mincer equation and show that it does not change the results.

When we estimate the impact of droughts on the probability of an individual to be employed, we have preferred to use the linear probability model instead of a logit model. In a binary model, linear probability models are a convenient approximation of the response probability (Wooldridge, 2010). A linear probability model also enables us to take into account spatial correlation between workers from the same city, contrary to maximum-likelihood models.

When we estimate the impact of droughts on wages, hours worked and labour incomes, we provide sub-samples results for formal and informal workers. This sub-sample analysis is motivated by the hypothesis that informal workers are more exposed to shocks than formal ones due to social policies and labour laws in Latin America that protect formal workers but not informal ones. LABLAC classifies workers as informal if they are self-employed, if they work for a private small firm (a firm with less than five employees).

4. Empirical results

4.1. Main results

Table 1 shows our estimates of the impact of small (top panel) and large (bottom panel) abnormal dry events on the probability of being employed, on the logarithm of hourly wages, on the logarithm of the number of hours worked per month, and on the logarithm of monthly labour incomes.

Column 1 presents the results of the impact of droughts on the probability of active individuals to be employed. They suggest that small dry deviations repeated over time impact the level of employment. Small sustained dry shocks decrease employment by 0.4 percent. Large shocks sustained over two months decrease the probability of active individuals to be employed by 1.5 percent compared to a near normal weather period; a point estimate four times larger than for small dry shocks.

Columns 2 to 10 focus on labour market outcomes of employed workers. We find that shocks lasting for only one month have almost no impact on labour market outcomes. Small shocks that last for one month affect the number of hours worked by formal workers only. This impact on hours worked is economically limited (+0.6 percent). Assuming that an individual works 40 h a week in a normal schedule, our result means that the number of hours worked will decrease by 0.6 percent of forty hours: 15 min. Consequently, with the hourly wage remaining constant, the increase in hours worked by formal workers does not translate into an increase of their monthly labour incomes. As for large shocks lasting for one month, we do not find statistical evidence that they affect labour market outcomes.

When abnormal levels of rainfall are sustained over time (i.e., the definition of droughts), labour market outcomes of employed workers are impacted. It is particularly true for informal workers.

Table 1
Droughts and Labour Market Outcomes.

	All Active	All Employed			Informal Employed			Formal Employed		
	Employment (1)	Wage (3)	Hours (4)	Labour Income (5)	Wage (6)	Hours (7)	Labour Income (8)	Wage (9)	Hours (10)	Labour Income (11)
Panel A : Small deviations										
Drought 1 month	0.001	−0.004	0.002	−0.003	−0.001	−0.003	−0.004	−0.005	0.006***	0.001
	(0.001)	(0.011)	(0.004)	(0.008)	(0.008)	(0.009)	(0.007)	(0.010)	(0.002)	(0.009)
Drought 2 months	−0.004**	−0.033	0.015**	−0.018	−0.029**	0.036**	0.006	−0.030	0.009**	−0.021
	(0.002)	(0.036)	(0.006)	(0.032)	(0.013)	(0.014)	(0.010)	(0.033)	(0.004)	(0.031)
Temperature	0.000	0.004*	−0.000	0.004**	0.002	0.001	0.003**	0.004*	−0.001	0.003**
	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lag 1 Temperature	−0.000	−0.008*	0.001	−0.007*	−0.006**	0.002	−0.005***	−0.008*	0.002	−0.007*
	(0.000)	(0.004)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.001)	(0.004)
Panel B : Large deviations										
Drought 1 month	−0.002	0.008	−0.003	0.005	−0.009	0.003	−0.006	0.031	−0.008	0.023
	(0.002)	(0.017)	(0.009)	(0.023)	(0.011)	(0.011)	(0.020)	(0.019)	(0.007)	(0.021)
Drought 2 months	−0.015***	−0.031	−0.028	−0.058*	−0.019	−0.045***	−0.064***	−0.026	−0.005	−0.031
	(0.003)	(0.023)	(0.017)	(0.030)	(0.021)	(0.014)	(0.020)	(0.026)	(0.022)	(0.030)
Temperature	0.000	0.004*	−0.000	0.004**	0.002	0.001	0.003**	0.004**	−0.001	0.003***
	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lag 1 Temperature	−0.000	−0.008*	0.001	−0.007*	−0.006**	0.002	−0.005***	−0.008*	0.002	−0.007*
	(0.000)	(0.004)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)	(0.001)	(0.004)
Observations	12,409,802	8,488,751	8,488,751	8,488,751	3,192,646	3,192,646	3,192,646	5,277,554	5,277,554	5,277,554

Notes: Standard errors in parentheses. *, ** and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (X_m) fixed effects. The significance of all test for droughts remains unchanged when following a Bonferroni procedure to account for multiple hypothesis testing.

Sustained small dry shocks decrease hourly wages of informal workers by 2.9 percent. This decrease is compensated by a similar increase in the number of hours worked (+3.6 percent), so that the monthly labour incomes of informal workers remain unchanged in the case of small sustained dry shocks.

Sustained large dry shocks have the most negative impact on employed workers. They lead to a decrease of the number of hours worked (−4.5 percent) of informal workers. Cumulated to a (non-significant) decrease in hourly wages (−1.9 percent), it translates into a significant decrease in labour monthly incomes. We estimate that large sustained dry events cause a 6.4 percent decrease in monthly labour incomes of informal workers. Informal workers in LABLAC are both workers from small firms and workers from informal firms. Formal workers are however not impacted by large and sustained shocks. This absence of impact on their wages was expected as formal workers in Latin America are typically protected by social laws. One could have however expected an impact on the number of hours they work.

Conducting multiple hypothesis testing inherently increases the risk of false-positive (Type I) errors compared to single hypothesis testing. The Bonferroni procedure is a widely used correction of standard errors that allows to control this problem while maintaining adequate power to correctly reject null hypotheses. It consists in correcting standard errors by the number of tests conducted. If one simultaneously tests for the significance of n coefficients and wants to reach a level of significance of α (generally 0,05), a level of significance of α/n needs to be attained to reject the null hypothesis of an absence of impact. In each regression reported in Table 1, we simultaneously test the significance of two coefficients. Consequently, we need to reach a p-value below 0,025 to correctly reject a null hypothesis at a 0,05 level. All coefficients for informal workers pass the test, limiting fears of spurious correlations.

4.2. Robustness

We report in Appendix several robustness checks. The standard equation in labour economics to explain wages is the Mincer equation that includes the gender, the age, the square of age and education as control variables. Because dry shocks are by construction exogenous, we do not need to control for these variables. We show in Table A2 that adding these control variables in the regression does not change our results.

In addition, as we focused on the rounds of surveys that are representative at the city level, we can collapse our database by city to have an aggregate measure of economic condition at the city level. We construct a city-month panel on the average values of labour market incomes and estimate it by specifying a full panel structure with city and month by year fixed effects. Results are reported in Appendix A3. We find results consistent with our main specification, particularly for large repeated shocks. The average probability of an active individual to be employed decreases with large repeated dry shocks (−0.8 percent), but do not decrease with small repeated shocks anymore. For employed workers, the number of hours worked decrease (−3.3 percent), leading to a decrease in labour incomes (−4 percent).

By construction, four consecutive months of small dry shocks bring a similar decrease in rainfall than two consecutive large shocks. As a robustness check, we also measure droughts by counting the number of deviations larger than one standard deviation up to four months instead of two as before. We display results in Table 2. We find little evidence that deviations up to four months impact the probability of employment. As opposed to Table 1, the probability of being employed increases by 0.3 percent with one month of dry shock. However, this result is statistically significant only at a 10 percent level and is no more significative if we correct standard errors for multi hypothesis testing. Consistently with Table 1, dry shocks that last over one month impact workers only marginally. When dry shocks are repeated over two months, wages of informal workers decrease (−3percent). This decrease is compensated by an increase in the number of hours worked (+7.5 percent). When shocks last for three months, informal workers' wages also decrease (−5.5 percent). This result is also true when shocks last for four month. Interestingly for four months, formal workers also are impacted.

Our results suggest that formal workers' wages decrease by 13 percent while their number of hours worked increase by 4.3 percent, leading to a decrease of labour incomes of 8.7 percent. This result differs from Table 1 where formal workers were not impacted by droughts.

To be consistent with the economic literature, we have constructed our shocks variables based on the empirical long-term

Table 2
Droughts and Labour Market Outcomes -Small variations sustained over four months.

	All Active	All Employed			Informal Employed			Formal Employed		
	Employment (1)	Wage (3)	Hours (4)	Labour Income (5)	Wage (6)	Hours (7)	Labour Income (8)	Wage (9)	Hours (10)	Labour Income (11)
Drought 1 month	0.003*	−0.015	0.009***	−0.006	−0.002	0.010	0.009	−0.018***	0.009***	−0.009*
	(0.002)	(0.010)	(0.003)	(0.008)	(0.011)	(0.010)	(0.006)	(0.006)	(0.002)	(0.005)
Drought 2 months	−0.000	−0.033	0.031***	−0.002	−0.030***	0.075***	0.045**	−0.029	0.010	−0.018
	(0.002)	(0.035)	(0.009)	(0.033)	(0.008)	(0.023)	(0.021)	(0.030)	(0.007)	(0.030)
Drought 3 months	0.000	−0.018	0.016**	−0.002	−0.055**	0.027	−0.028	−0.009	0.015***	0.006
	(0.004)	(0.025)	(0.008)	(0.026)	(0.022)	(0.019)	(0.028)	(0.028)	(0.005)	(0.026)
Drought 4 months	−0.004	−0.090***	0.008	−0.082**	−0.056***	−0.008	−0.064	−0.130**	0.043**	−0.087**
	(0.009)	(0.032)	(0.025)	(0.032)	(0.015)	(0.031)	(0.040)	(0.050)	(0.018)	(0.040)
Temperature	0.000	−0.000	0.000	0.000	−0.001	−0.001	−0.002	−0.000	0.001*	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Lag 1 Temperature	−0.001	0.001	0.001	0.002	−0.001	0.003	0.002	0.001	−0.000	0.000
	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
Lag 2 Temperature	−0.000	−0.005***	−0.002*	−0.007***	0.001	−0.003*	−0.002	−0.003**	−0.001	−0.004***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Lag 3 Temperature	0.000	−0.004	0.001**	−0.003	−0.005	−0.000	−0.005	−0.005*	0.003***	−0.003
	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
Observations	9,622,357	7,675,744	7,675,744	7,675,744	2,971,277	2,971,277	2,971,277	4,685,584	4,685,584	4,685,584

Notes: Standard errors in parentheses. *, ** and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (X_m) fixed effects. The significance of all test for droughts remains unchanged when following a Bonferroni procedure to account for multiple hypothesis testing.

Table 3
Wet spells and labour market outcomes.

	All Active	All Employed			Informal Employed			Formal Employed		
	Employment (1)	Wage (3)	Hours (4)	Labour Income (5)	Wage (6)	Hours (7)	Labour Income (8)	Wage (9)	Hours (10)	Labour Income (11)
Panel A : Small deviations										
Wet spell 1 month	0.000	-0.015^{***}	0.002	-0.013^{***}	-0.019^{***}	0.004	-0.015^{***}	−0.004	0.002	−0.002
	(0.002)	(0.005)	(0.002)	(0.005)	(0.005)	(0.003)	(0.005)	(0.004)	(0.003)	(0.002)
Wet spell 2 months	0.002	0.007	0.012^{**}	0.019^{*}	−0.008	0.024	0.016	0.015	0.003	0.018
	(0.003)	(0.009)	(0.006)	(0.011)	(0.010)	(0.016)	(0.012)	(0.016)	(0.003)	(0.016)
Temperature	0.000	0.004^{*}	−0.000	0.003^{**}	0.002	0.001	0.003^{**}	0.004^{**}	−0.001	0.003^{***}
	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lag 1 Temperature	−0.000	-0.008^{*}	0.002	-0.007^{*}	-0.006^{**}	0.002	-0.005^{***}	-0.008^{*}	0.002	-0.007^{*}
	(0.000)	(0.004)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)	(0.001)	(0.004)
Panel B : Large deviations										
Wet spell 1 month	0.001	−0.018	−0.004	−0.022	0.007	-0.030^{**}	-0.023^{*}	-0.037^{*}	0.008^{*}	-0.029^{*}
	(0.002)	(0.014)	(0.003)	(0.014)	(0.005)	(0.012)	(0.012)	(0.019)	(0.004)	(0.015)
Wet spell 2 months	0.001	−0.009	0.003	−0.006	-0.036^{***}	0.011	-0.025^{**}	0.007	−0.007	−0.001
	(0.002)	(0.011)	(0.005)	(0.014)	(0.013)	(0.017)	(0.011)	(0.018)	(0.005)	(0.014)
Temperature	0.000	0.004^{*}	−0.000	0.004^{**}	0.002	0.001	0.003^{**}	0.004^{**}	−0.001	0.003^{***}
	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lag 1 Temperature	−0.000	-0.008^{*}	0.001	-0.007^{*}	-0.006^{**}	0.002	-0.005^{***}	-0.008^{*}	0.002	-0.007^{*}
	(0.000)	(0.004)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)	(0.001)	(0.004)
	12,409,802	8,488,751	8,488,751	8,488,751	3,192,646	3,192,646	3,192,646	5,277,554	5,277,554	5,277,554
Observations	12,409,802	8,488,751	8,488,751	8,488,751	3,192,646	3,192,646	3,192,646	5,277,554	5,277,554	5,277,554

Notes: Standard errors in parentheses. *, ** and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (X_m) fixed effects.

distribution of local precipitations. Meteorologists have developed different indexes to measure droughts. The Standard Precipitation Index (SPI) is arguably the most popular among them (McKee, Doesken and Kleist, 1993). The SPI is similar to our main definition of shocks at the exception that the original distribution of rainfall data is fitted to a gamma distribution in a first step. Also, the SPI can be calculated for deviations over several months. We test the robustness of our results using the SPI.

We compute a one month and two months SPI based on Willmott, Matsuura and Legates (2001)'s data using the *precintcon* package in R. We follow the National Climatic Data Center classification of droughts to construct small and large shocks. Small shocks are defined for SPI between −0.5 and −1.3 (abnormally to moderately dry events). Large shocks are defined for SPI below −1.3 (very to severely dry events). We report the results in Table A4. They confirm that dry shocks negatively affect labour incomes, particularly large sustained dry shocks in an order of magnitude similar to Table 1. For large droughts, results suggest that even formal workers are impacted while they were not using the original definition of droughts. Large dry shocks lasting one month decrease labour incomes of formal workers by 2.6 percent. When large shocks last for two months, the decrease in labour incomes is of 4.6 percent. Overall, these robustness checks indicate that results presented in Table 1, notably regarding the impact of large sustained dry shocks, are valid using different specifications and they all provide estimate of a similar magnitude.

4.3. Wet shocks and labour market outcomes

How labour markets respond to wet shocks? We replace droughts by their symmetric wet spells in Table 3. As oppose to droughts, our estimates suggest that wet shocks do not affect the level of employment, whether the shocks are small or large, short or sustained over time.

For employed workers, one month small wet spells decrease hourly wages workers by −1.9 percent and labour incomes of informal by 1.5 percent. As for large wet spells (the kind of deviation leading to floods), they affect both formal and informal workers. Large wet spells lasting over one month decrease the hourly wage of formal workers by 3.7 percent labour incomes by 2.9 percent. These coefficients are however significant only at a 10 percent level. Informal workers see a similar decrease in labour income with one-month large wet shocks (2.3 percent) but at a 10 percent significance level as well. When large wet spells are sustained over time, the decrease in labour income is of the same order of magnitude (−2.5 percent), but this time driven by a decrease in hourly wages instead of the number of hours worked. Hence, if wet spells do not impact the general level of employment as opposed to droughts, there is suggestive evidence that they can impact the welfare of employed workers. The total impact of wet spells on labour incomes is smaller than the impact of dry shocks.

Latin America is a data rich region. In Appendix 5, we provide additional robustness checks using alternative sources of data covering different cities, and different time periods. We show that our results are consistent if we use harmonised household surveys for Argentina, Brazil and Colombia between 1992 and 2014, if we use enterprise surveys for 22 Latin American and Caribbean countries from the 2010 round that includes GPS coordinates. Results are also consistent when using administrative data on the universe of firms in Brazil between 2000 and 2013.

5. Pathways

We investigate two pathways that could drive the results: an increase in the number of power outages due to droughts, and a worsening of health conditions.

5.1. Droughts and power outages

Generating electricity is highly water intensive (Fthenakis & Kim, 2010) and several examples over the last years have highlighted the threat water scarcity can represent for electricity provision in the region.[7] When excessive rainfall is followed by floods or landslides, large wet shocks might also cause an increase in power outages because of the damages on infrastructures. We use enter-

[7] For instance, Brazil's power sector is dominated by hydropower, which accounts for two-thirds of the total installed capacity. Heavy dependence on hydropower makes Brazil vulnerable to power-supply shortages in the case of long periods of drought.

prise surveys to explore the link between droughts and the occurrence of water outages for firms.

Enterprise Surveys are harmonised firms surveys conducted by the World Bank. They contain data for formal private manufacturing firms with five or more employees. The firm level data is representative at the national level based on random stratified sampling with sector, size, and location being the strata. The survey targets business owners and top managers of firms as respondents. We compile for this analysis Enterprise Surveys from all available LAC countries for which GPS coordinates are available. The sample covers 22 LAC countries and has data for 2010. The Enterprise Surveys data has several advantages including being comparable across countries. The surveys cover a wide range of topics on the business environment that typical census firm level data does not include. Of primary interest for us, the enterprise surveys provide information on the occurrence of electricity outages experienced by firms. We use this information to test if rainfall shocks cause an increase in power outages. We test the model:

$$Power\ Out_{i,j,k} = \alpha + \beta_1 1SD_j^+ + \beta_2 2SD_j^+ + \beta_3 1SD_j^- + \beta_4 2SD_j^- + \tau_1 Temperature_j + \gamma_1 Country_k + \epsilon_{i,j}$$

where $PowerOut_{i,j,k}$ is the typical number of power outages experienced by firm i in region j from country k during a month of the year 2010. Enterprise surveys being annual, we construct our shocks variables by counting the number of months with weather deviations during the year and we treat the variables as continuous variables. Results are displayed in Table 4. We consistently find that large shocks increase the number of power outages in Latin America. An additional month with large dry shock during the year increase the number of power outages by 0.7, which correspond to a 33 percent increase. This impact of large dry shocks is two times larger than the impact of large wet shocks (+0.2 to +0.29). When controlling for firms' characteristics for robustness, results also suggest that small abnormal deviations increase the number of power outages. The increase in outages is however ten times lower with small shocks than with large shocks, accrediting that it is not passed on to labour market outcomes.

Table 4
Droughts and power outages in Latin America.

	Shocks	Shocks + controls
Total Number of Negative 1 SD Prec shocks	0,003	0,006**
	(0,003)	(0,003)
Total Number of Negative 2 SD Prec shocks	0,070***	0,075***
	(0,023)	(0,014)
Total Number of Positive 1 SD Prec shocks	0,002	0,004
	(0,003)	(0,004)
Total Number of Positive 2 SD Prec shocks	0,029***	0,030***
	(0,007)	(0,006)
Average Monthly Temp for the Year	0,0001	−0,0002
	(0,000)	(0,001)
Number of observations	7 610	4 303

Notes: Standard errors in parentheses. *, ** and *** indicate significance at the 10, 5, and 1% level, respectively. All specifications include country, and sector 2-digits fixed effects. In column 2, firms' level controls are: Firms own a generator (Y/N), Bribery depth (% of public transactions where a gift or informal payment was requested), Bribery incidence (Firms experiencing at least one bribe payment request Y/N), Firm size (Log of total number of employees), % of firms buying fixed assets, Establishment has checking or savings account at this time, Establishment has a line of credit or loan at this time, Losses due to breakage/spoilage shipped domestically (% of value of the products), Security costs (% of sales), Log of age of firm, Gender of the manager, Nationality of ownership (foreign or not), Exports 10% or more of sales, Number of years firm was unregistered at start, Use technology licensed from foreign companies and a constant term.

5.2. Health

While Latin America enjoys relatively high water access (especially in urban areas), the quality and safety of water and sanitation infrastructure remain insufficient – particularly in terms of sanitation. Indeed, sewerage access is low and less than 30 percent of wastewater is being treated, an inadequate level given the level of income and urbanization of the region. The health consequences of those access gaps are tangible (Forouzanfar et al., 2016).

Incidentally, health ranks high in terms of the potential pathways through which droughts may affect households and workers through a deterioration of the quality of their environment leading to a higher risk of contamination and a higher occurrence of epidemic diseases. This pathway could be a direct one, impacting the health of the income earner, or an indirect one resulting from the need to care for another sick person (child, family member etc.).

We construct a dataset on health outcomes using hospital micro data from Brazil (Datasus) between 2000 and 2013 to study this pathway. The dataset records hospital admissions every month over the period, representing about 39.5 million patients and provides information on, among other, the reasons of the admission of the patient. We collapse the data to construct a monthly panel at the municipality level (the lowest administrative division in Brazil). The administrative division used for the panel is the municipality where the hospital is located, and not the municipality where the patient lives. As our focus is on urban areas and most urban areas have at least one hospital within their boundaries limits, it is unlikely that the households would go to a hospital located in a different municipality than the one where they reside.[8] It is also unlikely that they go in a hospital located in a city far from the one where they live. Hence, the municipality of the hospital is experiencing the same weather than the municipality of residence of the patient.

We merge Datasus with official population counts provided annually by the Brazilian Institute of Geography and Statistics (IBGE), and with the Brazilian weather dataset by Xavier, King, and Scanlon (2015). This weather dataset is available at a finer scale than Willmott et al. (2001) (0.25 $\times$ 0.25 degree) and is arguably, more precise thanks to the use of 3625 rain gauge and 735 weather stations. Our focus for this paper being urban areas, we classify a municipality as an urban one if its urban population is larger than its rural population.

To estimate the impact of shocks on health outcomes, we use municipality and month by year fixed effects to control for unobserved fixed characteristics and time variations. The model estimated is:

$$\ln(Health\ Outcome)_{i,t} = \beta\, Drought^k_{i,t} + \tau_1 Temperature_i + \gamma_i + \mu_t + \epsilon_{i,t}$$

On the left-hand side, we focus on the logarithm of hospital admissions. We limit the analysis to admissions not related to alcohol consumption, diabetes or for psychiatric reasons. Following the medical literature, we also focus on diarrhea cases for which we have information for children under two years old and that is expected to be influenced by rainfall through an increased environmental contamination. As those cases are registered at the hospital level, they are likely to be more severe, having required parents to bring their child to the hospital. There are good reasons to believe that a spike in diarrhea cases at hospital level is likely echoed by a corresponding if not larger incidence of diarrhea in children not

[8] With the possible exception of households living close to the border of another municipality. However, as a number of social programs have a municipal focus, households are likely to indeed attend facilities located in their municipality of residence.

Table 5
Droughts and health outcomes.

	Admissions (1)	Diarrhea (2)	Admissions - Urban (3)	Diarrhea - Urban (4)
Panel A				
Small dry shock	0.006***	0.012***	0.006*	0.004
	(0.002)	(0.003)	(0.003)	(0.004)
Temperature	−0.012***	−0.013***	−0.014***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Panel B				
Large Dry shock	0.038*	0.052*	0.048*	0.059*
	(0.022)	(0.028)	(0.027)	(0.034)
Temperature	−0.011***	−0.013***	−0.014***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Panel C				
Small wet shock	0.002	0.013***	0.005	0.012***
	(0.002)	(0.003)	(0.003)	(0.004)
Temperature	−0.011***	−0.013***	−0.014***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Panel D				
Large wet shock	−0.003	0.012***	−0.001	0.022***
	(0.003)	(0.005)	(0.004)	(0.006)
Temperature	−0.011***	−0.013***	−0.014***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	852,857	754,037	549,289	475,372
Number of Municipalities	5,49	5,484	3,544	3,541

requiring hospitalization but likely disruptive for their parents' time allocation and thus a good proxy for this health pathway. Variables on the right-hand side are similar to Eq. (1), already defined this time with the Brazilian weather data.

Our results support this pathway (Table 5). They confirm that shocks, and particularly droughts, increase the number of hospital admissions in Brazil. The effect of small dry shocks and large dry shocks on both hospital admission and the number of case of diarrhea are significant, even if mostly urban areas. The effect of contemporary small shocks is at least five times lower than the impact of large dry deviations. Small dry shocks lead to 0.6 percent increase in hospital admissions in both rural and mostly urban municipalities, and to a 1.2 percent increase in the cases of diarrhea. This impact on diarrhea cases is however not significant when limiting the analysis to mostly urban municipalities. Large dry shocks increase the number of hospital admissions in Brazilian municipalities by 3.8 percent as compared to a near normal weather month, and even by 4.8 percent when focusing on mostly urban municipalities. They also increase the number of cases of diarrhea by 5.2 percent compared to near normal weather year in an average Brazilian municipality, and by 5.9 percent in a mostly urban municipality. Interestingly, when looking at the impact of similar wet shocks, we find a smaller impact. Small or large wet shocks lead to 1.2 increase in the number of diarrhea. The increase if of 2.2 percent when shocks are large in mostly urban municipalities. We however do not see an impact of wet shocks on the level of admissions.

6. Discussion and conclusion

Conventional wisdom among policymakers is that droughts can have severe economic consequences in rural areas, but only a limited impact in cities. Economic activities that are less directly reliant on water than agriculture, and better infrastructures are believed to buffer cities' economies against negative rainfall variations. Instead of that, the conventional wisdom is that cities should protect themselves against floods and their harmful impact. The results presented in this paper challenge this view: it turns out that droughts are costly realities in cities. We have highlighted that cities' economies are sensitive to droughts, even in the best endowed region in terms of infrastructures among the developing regions, Latin America. When a drought hits a city, our findings indicate that the probability of being employed for active inhabitants decreases by one percent. The labour incomes of informal workers decrease on average by six and a half percent because of a decrease in the number of hours worked when the shocks are large, and because of a decrease in hourly wages when shocks are smaller but repeated over a longer period of time. Maybe surprisingly and so far undocumented, our results suggest that the impact of droughts on labour market outcomes is larger than the impact of wet shocks, including wet shocks of an intensity that can cause floods. Our investigation of possible pathways suggests that a decrease in productivity explains at least partly the results. An increase in power outages and a deterioration of workers' health during droughts are two mechanisms through which productivity declines.

In our results, informal workers are more affected by droughts than formal workers but it does not mean that the formal sector is not impacted by droughts. In Latin America, social laws are particularly protective for formal workers. It is then unlikely that firms decrease their workers' wages or the number of hours worked by workers. Consequently, strong social laws for formal workers might explain why we see an impact of droughts on informal workers more than on formal workers. Our results however confirm that firms operating with formal workers slow down new hires during droughts. Formal firms are then also impacted, even if their current workers are not.

Because informal workers are more affected by droughts than formal workers, droughts have redistributive impacts and have consequences for poverty reduction. In Latin America, informal workers are more likely to be poorer than the rest of the population (Table A6). Therefore, droughts predominantly impact poor and vulnerable households. Labour incomes in Latin America are a key tenant of poverty reduction. Our finding of an eight percent decrease in labour incomes for informal workers during droughts is consequently preoccupying for poverty reduction, particularly in the current context of the economic slowdown of the region.

If our results of a decrease in labour incomes and of a decrease of the probability of obtaining a job seem to be explained by a

decrease in productivity of firms and workers, other mechanisms could also be at play, such as rural to urban migrations. A drought in rural areas affecting yields directly could push workers to migrate into cities, as documented in the literature for some part of the world (Henderson et al., 2017). Workers newly arrived from rural areas can be expected to be less qualified. That on top of an increase in labour offer could decrease wages and the probability of being employed in the short term. In that case, our results of a worsening of labour market outcomes for workers would suggest that cities are impacted by droughts because surrounding rural areas are themselves impacted by droughts. We do not believe that this mechanism explains our results for several reasons that we detail here. First, the droughts studied in our paper are measured in cities. They are not measured in surrounding rural areas where agriculture occurs. In addition, the cities included in our paper are the region's largest metropolitan areas. For these large cities, the closest farms often locate far from them and the weather we observe in cities in our data is therefore likely to be different from the weather experienced by the closest farmers. Hence, our paper does not measure what is happening in rural areas where droughts would occur but in urban areas. Second, rural to urban migrations caused by droughts have been documented for Africa (Henderson et al., 2017) or for the Caribbean (Baez et al., 2017), two regions where farmers differ largely from farmers in Latin America. Indeed, a family farm in Latin America covers on average 50 ha of lands, more than in Africa or in the Caribbean, and is particularly more mechanised (Berdegué, 2011). The cost of disinvestment to migrate into cities is therefore higher in Latin America than in Africa or in the Caribbean, making Latin American farmers less likely to migrate to towns. Importantly as well, the countries included in our analysis are predominantly urban. While rural to urban migration was important to the growth of cities up until the turn of the 21st century,[9] immigration rates significantly slowed down since the 1980s (Da Cunha, 2003). Many migrants stopped leaving States that were previously characterised by high emigration rates and instead moved to areas within their own states towards smaller cities (e.g., Minas Gerais and Paraná in Brazil). Accordingly, Thiede, Gray, and Mueller (2016) find no consistent impact of droughts on migration in Latin America, using census data between 1970 and 2011. Third, even if some rural-urban migration would occur, the literature on the impact of migration on labour market outcomes is unsure about the consequences of migration. In his seminal paper, Card (1990) demonstrates that the arrival of Cuban migrants in Florida has not lead to any change in wages or employment. Friedberg (2001) even indicates that the sudden expansion of the labour force in Israel between 1989 and 1995 caused by the arrival of Soviet Jewish immigrants has increased and not decreased earnings. In addition, when migration had increased unemployment, the effects are smaller than in our results (Hunt, 1992; Kleemans & Magruder, 2017), or localised in specific sectors (e.g. the construction sector in Carrington and De Lima (1996)).

Looking forward, our work highlights areas needing further research. First, health and power outages might not be the only pathways explaining this impact of droughts. If agriculture is the thirstiest economic sector, other sectors rely on water for their production activities. Such sector can include manufacturing, construction or mining firms. It might be the case that because of water outages, these firms are directly impacted by droughts. This question is hard to investigate with our data. The surveys we use are representative at a city level. They are not meant to be representative for each sector. Additional research based on administrative data on firms instead of survey data would allow researchers to study firms' dynamics by sector and see if sectors that are relatively more water intensive are more affected by droughts.[10]

Second, beyond metropolitan areas and "primate cities" (Jefferson, 1939) a need exists to also look at the exposure and impact of secondary cities and small towns, that are less well endowed with infrastructure and where poverty tends to be higher (Ferré, Ferreira, & Lanjouw, 2012). As noted by Christiaensen and Kanbur (2017), not only do two-fifths of the urban population live in small towns of less than 250,000 but urban centres of less than one million will absorb the majority of the population growth in coming years (Laros & Jones, 2014). Fay, (2017) also flag this issue as important for the region in light of the evolution of its urbanization patterns. With dwindling density already observed in some of the large metropoles of our analysis (Buenos Aires, Brasilia, Santiago, or Montevideo among others) as a result of transport, land use and housing policies, the implications for infrastructure investments and maintenance costs in a context of higher climate variability are ever more pressing and foreboding for other regions.

Third, our results confirm the need to understand better the role of water and sanitation infrastructure in weathering climate variability and water stress in low and middle-income countries. This issue of urban water infrastructure has been raised in the water resource management literature (McKinsey, 2009). At the exception of Ashraf et al. (2017), the economic literature notably lags in terms of research that could shed light on the type of infrastructure and the level of coverage required not only to respond to the demand of cities, but also to absorb water variability. Beyond infrastructures, ensuring abundant and safe water in cities also requires to better manage water all along its cycle, from its source to the tap. Water scarcity downstream is often linked to land use changes upper in the basin, the most harmful of these changes being often deforestation. In addition, ensuring abundant water in cities does not only require supply-side investments but demand-side policies and a better regulation of water utilities (Damania et al., 2017).

Conflict of interest

The authors declare no conflict of interest.

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Appendix A

Additional robustness checks using alternative datasets

Household surveys

We use for our main results multiple rounds of labour force surveys compiled by the CEDLAS project. The CEDLAS project has also harmonised household surveys through the Socio-Economic Database for Latin America and the Caribbean (SEDLAC) initiative. As

[9] For instance in Brazil, this rural to urban migration started to decrease in the 1970s. Areas that had previously attracted large numbers of people (the central west and São Paulo).

[10] The RAIS data we had access to for this work for does not indicate the sector in which firms operate.

opposed to labour force surveys that are monthly, households surveys in SEDLAC are annual. Identification of a direct impact of droughts on labour market outcomes is therefore less precise. Labour market outcomes in SEDLAC are recall question on wages, earnings and hours worked during a typical month of the past calendar year. Data hence mix information on Labour Outcomes during the shock and during the recovery period. As a third robustness check, we compile all the rounds of SEDLAC surveys that are representative at the metropolitan area level to confirm LABLAC results. The dataset covers around 2,000,000 active employed individuals living in 56 metropolitan areas in three countries (Argentina, 1998–2012; Brazil, 1992–2012, and Colombia, 2008–2014).

We construct shocks variables as the number of months with shocks during a year, and treat them as continuous variables. As in Eq. (1), we control for annual temperature, and we add year and cities fixed effects. Results are displayed in Table A5.1. As with LABLAC, small negative shocks are found to have no impact of Labour Outcomes. Large dry shocks them have an impact. An additional large dry shock decreases labour incomes by 4.6 percent. As for wet shocks, small wet shocks are associated with a small increase in labour incomes (+0.7 percent). Large wet shock decreases labour incomes by a bit more than one percent. Hence consistently with LABLAC, the negative impact of large dry shocks is four times larger than the impact of large wet shocks.

Contrary to LABLAC, non-labour incomes are consistently reported in SEDLAC, allowing us to look at the impact of shocks on them. Because a high proportion of non-labour incomes are public transfers (social transfers, pensions etc.),[11] we expect them to be less sensitive to shocks. Table A5.1 shows that small dry shocks do not decrease non-labour incomes. As for large dry shocks, they once again do decrease non-labour incomes. For all small shocks and for large wet shocks, non-labour incomes do not vary following shocks. Non-labour incomes do not decrease because of the shocks but neither do they increase to buer the negative impact of large wet shocks on labour incomes. Thus, the combined total incomes decrease with large wet shocks (i.e., negatively affected labour income and stable non-labour incomes). In the case of large dry shocks, the situation is worse. For informal workers, non-labour incomes significantly decrease after large dry shocks. Our analysis suggests that the impact on non-labour incomes is up to two times larger than the impact on labour incomes. Their total incomes are then affected by both a decrease in labour and non-labour incomes.

Firms data

Results in Table 1 suggest that droughts have an impact on employment levels in urban areas, but that wet spells have no impact on employment. We also find that formal workers' wages are greatly unaffected by droughts in LABLAC, confirming that if firms are impacted, they had to decrease their margins or slow down their growth. We confirm this by looking at the impact of droughts using firms data from harmonised surveys of the LAC region, and from administrative sources in Brazil.

Using enterprise surveys, we specify our model as follows:

$$EmpGrowth_{i,j,k,r} = \alpha + \beta_1 1SD_j^+ + \beta_2 2SD_j^+ + \beta_3 1SD_j^- + \beta_4 2SD_j^- + \tau_1 Temperature_j + \lambda \ln(Size)_{i,j,r} + \gamma_{1,k} + \gamma_{2,r} + \epsilon_{i,j,k,r}$$

where *EmpGrowth* is the annual growth in employment for firm i located in region j from country k and sector (within manufacturing) r between the fiscal year referenced in the survey (l1) and the two fiscal years preceding it (l2). The growth rate is calculated as (l1 − l2)/(l1 + l2)/2. Our main precipitation shock variables are the number of months a firm has experienced precipitation one and two standard deviations below and above the long run average precipitation during l2. Precipitation shocks are taken for the beginning of the period of the employment growth, as it is more likely to be a predictor of growth of total employment. We also control for temperature during l2. As in a standard growth equation, we account for the size of the firm in terms of total employment two fiscal years ago (ln(*Size*)). This is because employment two fiscal years ago is more likely to be a predictor of employment growth, than total employment in the last fiscal year. Finally, we include country and two-digit level ISIC sector (within manufacturing) fixed effects. Our identification strategies for shocks relies here on the differences in rainfall between firms from the same sector inside a given country.

Enterprise surveys provides information on the quality of water infrastructures firms enjoy. In an extended specification, we control for these infrastructures and study the correlation between the occurrence of water outages and employment growth. In this setting, we control for several firm characteristics to avoid an omitted variable bias. They include the age of the firm, foreign ownership, exporter status, security cots, generator ownership, and relationship to the informal sector in terms of competition, and whether the firm was informal before becoming formal.

[11] Pensions and transfers account for two-third of total non-labour incomes in our LABLAC database.

Table A1
Rounds of Surveys LABLAC and Enterprise Surveys.

	LABLAC		Enterprise Surveys Annual Data
	Monthly Data		
Countries	Number of Cities	Years	Year
Argentina	–	–	2010
Belize	–	–	2010
Bolivia	–	–	2010
Brazil	6	2005–2014	2010
Chile	9	2010–2014	2010
Columbia	22	2008–2014	2010
Costa Rica	–	–	2010
Ecuador	5	2006–2014	2010
El Salvador	1	2010–2013	2010
Guatemala	–	–	2010
Guyana	–	–	2010
Honduas	–	–	2010
Jamaica	–	–	2010
Mexico	32	2005–2014	2010
Nicaragua	–	–	2010
Panama	–	–	2010
Paraguay	1	2005–2014	2010
Peru	1	2005–2014	2010
Paraguay	–	–	2010
St. Vincent and Grenadines	–	–	2010
Surniname	–	–	2010
Trinidad and Tobago	–	–	2010
Uruguay	1	2006–2014	2010
Venezuela	–	–	2010
Total cities – firms	78		
Observations	12,230,393		
… Representing an average annual population of	308,885,074 (50% of the LAC population)		

Table A2
Droughts and Labour Market Outcomes – Augmented Mincer Equation.

	All Active	All Employed			Informal Employed			Formal Employed		
	Empl. (1)	Wage (3)	Hours (4)	Labour Income (5)	Wage (6)	Hours (7)	Labour Income (8)	Wage (9)	Hours (10)	Labour Income (11)
Small deviations										
Drought 1 month	0.001	0.001	0.002	0.003	0.003	0.000	0.003	−0.002	0.005***	0.003
	(0.001)	(0.004)	(0.003)	(0.003)	(0.007)	(0.009)	(0.006)	(0.003)	(0.002)	(0.004)
Drought 2 months	−0.003*	−0.014	0.017***	0.003	−0.021**	0.041***	0.020	−0.004	0.006	0.002
	(0.002)	(0.009)	(0.006)	(0.008)	(0.009)	(0.015)	(0.012)	(0.009)	(0.004)	(0.011)
Temperature	−0.000	0.001	−0.000	0.001	0.001	0.001	0.002**	0.001	−0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag 1 Temperature	−0.000	−0.004**	0.002	−0.002***	−0.005**	0.001	−0.004***	−0.003**	0.001	−0.002*
	(0.000)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Gender (man)	0.024***	0.205***	0.186***	0.391***	0.171***	0.260***	0.432***	0.166***	0.110***	0.277***
	(0.006)	(0.016)	(0.018)	(0.032)	(0.027)	(0.031)	(0.055)	(0.018)	(0.013)	(0.027)
Age	0.018***	0.040***	0.027***	0.067***	0.035***	0.030***	0.066***	0.040***	0.024***	0.064***
	(0.001)	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.005)	(0.005)	(0.003)	(0.005)
Age square	−0.000***	−0.000***	−0.000***	−0.001***	−0.000***	−0.000***	−0.001***	−0.000***	−0.000***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary incomplete	−0.006*	0.151***	0.031**	0.182***	0.103***	0.015	0.118***	0.123***	0.022***	0.145***
	(0.003)	(0.013)	(0.012)	(0.022)	(0.009)	(0.015)	(0.022)	(0.025)	(0.006)	(0.022)
Primary complete	−0.007*	0.290***	0.058***	0.348***	0.209***	0.050***	0.259***	0.235***	0.027***	0.262***
	(0.004)	(0.014)	(0.011)	(0.023)	(0.016)	(0.009)	(0.022)	(0.026)	(0.008)	(0.023)
Secondary incomplete	−0.012***	0.412***	0.056***	0.468***	0.274***	0.041***	0.315***	0.379***	0.016	0.395***
	(0.004)	(0.025)	(0.013)	(0.035)	(0.025)	(0.014)	(0.036)	(0.023)	(0.015)	(0.029)
Secondary complete	−0.011**	0.617***	0.084***	0.701***	0.408***	0.047***	0.455***	0.557***	0.010	0.567***
	(0.005)	(0.031)	(0.011)	(0.037)	(0.036)	(0.013)	(0.045)	(0.026)	(0.017)	(0.036)
College incomplete	−0.016**	0.936***	0.006	0.942***	0.687***	−0.098***	0.590***	0.848***	−0.072***	0.776***
	(0.007)	(0.036)	(0.015)	(0.045)	(0.059)	(0.030)	(0.076)	(0.029)	(0.015)	(0.026)
College complete	0.003	1.433***	0.036*	1.470***	0.862***	0.083***	0.946***	1.259***	−0.099***	1.159***
	(0.007)	(0.048)	(0.019)	(0.054)	(0.110)	(0.020)	(0.108)	(0.047)	(0.014)	(0.050)
Large deviations										
Drought 1 month	−0.001	0.000	−0.002	−0.001	−0.008	0.006	−0.002	0.013	−0.006	0.007
	(0.001)	(0.008)	(0.008)	(0.014)	(0.008)	(0.010)	(0.017)	(0.013)	(0.007)	(0.016)
Drought 2 months	−0.015***	−0.005	−0.029	−0.034*	−0.009	−0.049***	−0.058***	0.004	−0.007	−0.002
	(0.002)	(0.008)	(0.020)	(0.018)	(0.017)	(0.018)	(0.014)	(0.014)	(0.021)	(0.024)
Temperature	−0.000	0.001	−0.000	0.001	0.001	0.001	0.002**	0.001	−0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag 1 Temperature	−0.000	−0.004**	0.002	−0.002***	−0.005**	0.001	−0.004***	−0.003**	0.001	−0.002
	(0.000)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Gender (man)	0.024***	0.205***	0.186***	0.391***	0.171***	0.260***	0.432***	0.166***	0.110***	0.277***
	(0.006)	(0.016)	(0.018)	(0.032)	(0.027)	(0.031)	(0.055)	(0.018)	(0.013)	(0.027)
Age	0.018***	0.040***	0.027***	0.067***	0.035***	0.030***	0.066***	0.040***	0.024***	0.064***
	(0.001)	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.005)	(0.005)	(0.003)	(0.005)
Age square	−0.000***	−0.000***	−0.000***	−0.001***	−0.000***	−0.000***	−0.001***	−0.000***	−0.000***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary incomplete	−0.006*	0.151***	0.031**	0.182***	0.103***	0.015	0.118***	0.123***	0.022***	0.145***
	(0.003)	(0.013)	(0.012)	(0.022)	(0.009)	(0.015)	(0.022)	(0.025)	(0.006)	(0.022)
Primary complete	−0.007*	0.290***	0.058***	0.348***	0.209***	0.050***	0.259***	0.235***	0.027***	0.262***
	(0.004)	(0.014)	(0.011)	(0.023)	(0.016)	(0.009)	(0.023)	(0.026)	(0.008)	(0.023)
Secondary incomplete	−0.012***	0.412***	0.056***	0.468***	0.274***	0.041***	0.315***	0.379***	0.016	0.395***
	(0.004)	(0.025)	(0.013)	(0.035)	(0.025)	(0.014)	(0.036)	(0.023)	(0.015)	(0.029)
Secondary complete	−0.011**	0.617***	0.084***	0.701***	0.408***	0.047***	0.455***	0.557***	0.010	0.567***
	(0.005)	(0.031)	(0.011)	(0.037)	(0.036)	(0.013)	(0.045)	(0.026)	(0.017)	(0.036)
College incomplete	−0.016**	0.936***	0.006	0.942***	0.687***	−0.098***	0.589***	0.848***	−0.072***	0.776***
	(0.007)	(0.036)	(0.015)	(0.045)	(0.058)	(0.030)	(0.076)	(0.029)	(0.015)	(0.026)
College complete	0.003	1.433***	0.036*	1.470***	0.862***	0.083***	0.945***	1.259***	−0.099***	1.159***
	(0.007)	(0.048)	(0.019)	(0.054)	(0.110)	(0.020)	(0.108)	(0.047)	(0.015)	(0.050)
Observations	13,205,379	8,992,782	8,992,782	8,992,782	3,507,779	3,507,779	3,507,779	5,465,291	5,465,291	5,465,291

Notes: Standard errors in parentheses. *,** and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (X_m) fixed effects.

Results are presented in Table A5.2. They suggest that in the case of a small wet shocks, the rate of employment growth within firms slightly increases. The impact remains however economically limited. In the case of small dry shocks or large wet shocks, firms' hiring decisions do not seem to be impacted however. In contrast, and consistent with our previous results, when large dry shocks occur, firms slow down the hiring of new workers over the following year: firms' size growth rate is 14 percent to 23 percent slower during a year with a large dry shock compared to a normal year. The enterprise surveys also provide information on the number and length of water outages experienced by firms during the year of the survey. In line with previous results, the more frequent the water outages, the slower the growth of employment rate.

These results relying on enterprise surveys present the advantage of being regional. The cost of this purely-cross section approach is that we rely on spatial variations only to identify an impact, making harder to control for unobserved firms' characteristics. We show that these regional results on droughts for firms remain true when using panel data for Brazil.

Table A3
Droughts and Labour Market Outcomes – City panel.

	All Active	All Employed		
	Employment (1)	Wage (3)	Hours (4)	Labour Income (5)
Panel A : Small deviations				
Drought 1 month	−0.001	−0.007	−0.004	−0.010
	(0.001)	(0.009)	(0.003)	(0.009)
Drought 2 months	−0.001	−0.005	0.000	−0.005
	(0.002)	(0.017)	(0.005)	(0.016)
Temperature	−0.000*	0.009***	0.000	0.009***
	(0.000)	(0.003)	(0.001)	(0.002)
Lag 1 Temperature	−0.000***	−0.006***	−0.001	−0.007***
	(0.000)	(0.002)	(0.001)	(0.002)
Panel B : Large deviations				
Drought 1 month	−0.001	−0.032	0.013	−0.020
	(0.002)	(0.021)	(0.012)	(0.020)
Drought 2 months	−0.008***	−0.008	−0.033*	−0.040***
	(0.002)	(0.016)	(0.019)	(0.013)
Temperature	−0.000*	0.009***	0.000	0.009***
	(0.000)	(0.003)	(0.001)	(0.002)
Lag 1 Temperature	−0.000***	−0.006***	−0.001	−0.007***
	(0.000)	(0.002)	(0.001)	(0.002)
Observations	13,257,106	9,034,814	9,034,814	9,034,814

Table A4
Droughts and Labour Market Outcomes using SPI.

	All Active	All Employed			Informal Employed			Formal Employed		
	Employment (1)	Wage (3)	Hours (4)	Labour Income (5)	Wage (6)	Hours (7)	Labour Income (8)	Wage (9)	Hours (10)	Labour Income (11)
Panel A : Small deviations										
Drought 1 month SPI	−0.001	−0.003	−0.006**	−0.009*	−0.003	−0.007	−0.010	−0.004	−0.005***	−0.009*
	(0.001)	(0.005)	(0.003)	(0.005)	(0.007)	(0.004)	(0.006)	(0.005)	(0.002)	(0.005)
Drought 2 months SPI	−0.000	−0.006	−0.003	−0.008	0.005	−0.011	−0.006	−0.018*	0.003	−0.015*
	(0.001)	(0.007)	(0.004)	(0.008)	(0.005)	(0.007)	(0.007)	(0.010)	(0.004)	(0.008)
Temperature	0.000	0.003	0.000	0.003	0.000	0.001	0.002	0.003	−0.001	0.003*
	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Lag 1 Temperature	−0.000	−0.009*	0.001	−0.008*	−0.006**	0.001	−0.005**	−0.008*	0.002*	−0.007*
	(0.000)	(0.005)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)	(0.001)	(0.004)
Panel B : Large deviations										
Drought 1 month SPI	−0.005***	−0.013*	−0.004**	−0.018**	−0.003	−0.006	−0.009	−0.023*	−0.003	−0.026**
	(0.002)	(0.007)	(0.002)	(0.007)	(0.007)	(0.004)	(0.010)	(0.013)	(0.003)	(0.011)
Drought 2 months SPI	−0.002	−0.052**	−0.004	−0.055***	−0.027	−0.004	−0.031*	−0.047**	0.001	−0.046***
	(0.002)	(0.022)	(0.006)	(0.018)	(0.018)	(0.011)	(0.017)	(0.021)	(0.006)	(0.017)
Temperature	0.000	0.004	−0.001	0.002*	0.002	−0.001	0.001	0.005**	−0.001	0.004***
	(0.000)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Lag 1 Temperature	−0.000	−0.011**	0.002	−0.009**	−0.008*	0.003	−0.006*	−0.011**	0.002*	−0.009**
	(0.000)	(0.005)	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.001)	(0.004)
Observations	7,808,974	5,514,339	5,514,339	5,514,339	2,054,276	2,054,276	2,054,276	3,449,928	3,449,928	3,449,928

Notes: Standard errors in parentheses. *,** and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (X_m) fixed effects. The significance of all test for droughts remains unchanged when following a Bonferroni procedure to account for multiple hypothesis testing. Measures of droughts are this time based on SPI.

We construct a municipality-year panel recording the number of firms across Brazil using administrative data from the Annual Social Information Report (Relação Anual de Informações Sociais – RAIS). We access annual data between 2000 and 2013. Data being annual, we use the number of months with shocks during the year as our continuous drought variable as with SEDLAC and enterprise surveys. We estimate a fixed eect model as well as a dynamic fixed-effect model (Table A5.3). Using RAIS data, we find that even small shocks (both wet and dry) slowed down the general increase in the number of firms observed over the period in Brazil, even if the impact remains economically limited: an additional small shock is associated with a relative decrease in the number of firms by less than half percent. The effect is the largest for large dry shocks: an additional large dry shock during the year decreases the number of registered firms by about one percent to two percent.

This impact is again four time large than the impact of large wet shocks.

These results are consistent with our main results using LABLAC and SEDLAC data. Together, they indicate an economy-wide impact of large shocks (the workers and the firms); particularly in the case of droughts. Several pathways could explain this economically significant and consistent negative impact of large dry shocks. We explore two of them in the following section to provide an economic rationale for these results.

Table A5.1
SEDLAC.

	Labour Income						Non Labour Incomes					
	(1) Active Pop	(2) Informal	(3) Formal	(4) Self Employed	(5) Large Firms	(6) Small Firms	(7) Active Pop	(8) Informal	(9) Formal	(10) Self Employed	(11) Large Firms	(12) Small Firms
Small Positive Shocks	0.007*	0.009**	0.005	0.010**	0.007**	0.009**	−0.007	−0.007	0.001	−0.002	0.005	−0.007
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.012)	(0.008)	(0.018)	(0.010)	(0.017)	(0.010)
Small Negative Shocks	0.001	0.002	0.004	0.002	0.005	0.004	0.009	−0.006	0.020	−0.007	0.021	−0.007
	(0.004)	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)	(0.013)	(0.011)	(0.019)	(0.012)	(0.018)	(0.012)
Large Positive Shocks	−0.013**	−0.012*	−0.013**	−0.015*	−0.016***	−0.012*	−0.005	0.002	−0.010	0.005	0.000	−0.001
	(0.006)	(0.007)	(0.005)	(0.008)	(0.006)	(0.007)	(0.010)	(0.008)	(0.018)	(0.009)	(0.017)	(0.010)
Large Negative Shocks	−0.046*	−0.060*	−0.065**	−0.053	−0.061**	−0.067**	−0.071	−0.138***	−0.053	−0.103**	−0.116	−0.124**
	(0.028)	(0.033)	(0.029)	(0.039)	(0.024)	(0.033)	(0.054)	(0.044)	(0.070)	(0.044)	(0.072)	(0.053)
Average Temperature	0.077	−0.087	0.097**	−0.142**	0.084*	−0.066	−0.277**	−0.226**	−0.662***	−0.193*	−0.677***	−0.216**
	(0.063)	(0.065)	(0.047)	(0.067)	(0.050)	(0.070)	(0.119)	(0.107)	(0.200)	(0.099)	(0.219)	(0.109)
Av. Temperature sq	−0.002	0.001	−0.002**	0.002	−0.002*	0.001	0.006**	0.006**	0.015***	0.005**	0.016***	0.005**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)	(0.003)
Observations	2,086,298	780,249	1,078,798	413,161	710,774	869,033	319,095	129,712	113,469	70,749	63,712	147,213
Individual controls	No	No	No	No	No	No	No	No	No	No	No	No
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors clustered at the city-year level in brackets. Individual controls include: age of the respondent, gender, whether she/he is the household head, whether she/he is a formal worker and the sector (1 digit ISIC classification). ***: p < 0.01, **: p < 0.05, *: p < 0.1.

Table A5.2
Enterprise Surveys: Precipitation and Employment growth.

	Parsimonious	Firms controls + infrastructures
Total No of Positive 1 SD Prec shocks	2.970*	2.888**
	(1.694)	(1.389)
Total No of Positive 2 SD Prec shocks	−0.786	−0.389
	(1.644)	(1.829)
Total No of Negative 1 SD Prec shocks	−1.112	−0.773
	(1.238)	(0.896)
Total No of Negative 2 SD Prec shocks	−14.696***	−23.713***
	(4.944)	(6.181)
No of water shortages per day in a typical month		−7.960*
		(4.467)
Average duration of water shortage		−0.006
		(0.050)
Average Monthly Temp for the Year	1.677**	1.714**
	(0.709)	(0.685)
Square of Average Monthly Temp for the Year	−0.056***	−0.059***
	(0.022)	(0.022)
Constant	1.218	5.531
	(8.564)	(7.922)
Country Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Sector (2 digit) Fixed Effects	YES	YES
Number of observations	6351	5050

Note: Standard errors clustered following the design of the survey. ***: p < 0.01, **: p < 0.05, *: p < 0.1.

Table A5.3
A firms' perspective: shocks, employment growth and the creation of firms in Brazil using administrative data.

	Nb of firms	Nb of firms - Dynamic Panel
Lag 1 - Nb Firms		0.703***
		−0.01
Small Negative Shocks	−0.004***	−0.001**
	−0.001	−0.001
Large Negative Shocks	−0.016***	−0.008**
	−0.006	−0.003
Small Positive Shocks	−0.003***	0.001
	−0.001	−0.001
Large Positive Shocks	0.003**	0.002**
	−0.002	−0.001
lnPOP_Total	0.368***	0.098***
	−0.03	−0.014
Avg Temperature	0.043**	0.045***
	−0.019	−0.01
Avg Temperature sq	−0.001*	−0.001***
	0	0
Constant	1.146***	0.124
	−0.338	−0.165
Observations	53,929	50,835
City FE	Yes	Yes
Year FE	YES	YES
Number of municipalities	4010	3989

Cluster robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Urban: Urban Pop > Rural Pop.

Table A6
Who are the informal workers?

	LABLAC - Poor Less \$4	LABLAC - Vulnerable Less \$10
Age	−0.0134***	−0.0234***
	(0.00152)	(0.00201)
Gender	−0.948***	−0.858***
	(0.0483)	(0.0410)
Head of Household (0/1)	−0.540***	−0.494***
	(0.0297)	(0.0194)
Years of Education	−0.313***	−0.465***
	(0.0168)	(0.0160)
Type of contrat (Baseline: Formal worker)		
Informal Worker	0.483***	0.493***
	(0.0726)	(0.0794)
Type of firm (Baseline: Large firm)		
Small Firm	1.162***	0.479***
	(0.113)	(0.0891)
Public Firm	−0.414***	−0.492***
	(0.109)	(0.0702)
Salaried Worker	0.153	0.690***
	(0.140)	(0.127)
Self-Employed	1.132***	1.099***
	(0.130)	(0.153)
Not Salaried	−1.505***	−3.169***
	(0.553)	(0.543)
Constant	−2.282***	1.864***
	(0.175)	(0.233)
Year FE	YES	YES
City FE	YES	YES
Sector ISIC 1 FE	YES	YES
Observations	11,085,836	11,085,836

Notes: We present evidence that being an informal worker is positively associated with the probability of being a poor or a vulnerable individual in the LABLAC data (based on \$4 and \$10 poverty lines). Results here are from a logit regression. Standard-errors are clustered at the city-level. Additional controls include year, city and sector 1 digit fixed effects, and constant term. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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